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Using smartphone technology to reduce health impacts from atmospheric environmental hazards

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Abstract

Background: Global environmental change is exacerbating human vulnerability to adverse atmospheric conditions including air pollution, aeroallergens such as pollen, and extreme weather events. Public information and advisories are a central component of responses to mitigate the human impacts of environmental hazards. Digital technologies are emerging as a means of providing personalised, timely and accessible warnings.

Method: We describe AirRater, an integrated online platform that combines symptom surveillance, environmental monitoring, and notifications of changing environmental conditions via a free smartphone app. It was developed and launched in Tasmania, Australia (population 510 000), with the aim of reducing health impacts and improving quality of life in people with conditions such as asthma and allergic rhinitis. We present environmental data, user uptake and results from three online evaluation surveys conducted during the first 22 months of operation, from October 2015 through August 2017.

Results: There were 3,443 downloads of the app from all regions of Tasmania. Of the 1,959 individuals who registered, 79% reported having either asthma or allergic rhinitis. Downloads increased during adverse environmental conditions and following publicity. Symptom reports per active user were highest during spring (72%), lowest in autumn (37%) and spiked during periods of reduced air quality. In response to online surveys, most users reported that the app was useful and had improved their understanding of how environmental conditions affect their health, and in some cases had prompted action such as the timely use of medication.

Conclusion: Active engagement and consistent positive feedback from users demonstrates the potential for considerable individual, clinical and wider public health benefits from integrated and personalised monitoring systems such as AirRater. The perceived health benefits require objective verification, and such systems need to address several challenges in providing timely, reliable and valid environmental data.

Introduction and purpose

Global environmental change is exacerbating human vulnerability to atmospheric environmental hazards including air pollution, aeroallergens (such as pollen) and extreme weather events. For example, poor air quality and extremes of heat or cold cause exacerbations of heart, lung and other chronic conditions leading to increases in symptoms, hospitalisations and deaths [1–3]. Global environmental change increases the threat from these hazards in a number of ways. A warming climate has brought more frequent heatwaves and other extreme weather events, which interact with air pollution to increase population health risk [4]. For instance, wildfires driven by worsening fire weather, deforestation fires and fuel management burning are increasingly causing prolonged smoke pollution episodes in densely populated airsheds, iconic examples being California and southern Australia [5]. Furthermore, population exposures and resultant sensitization to aeroallergens have increased in many temperate landscapes in both the northern [6], and southern hemispheres [7] due to the global spread of plants known to be allergenic, through the lengthening of pollen seasons, and the increased abundance of pollens in response to anthropogenic climate change, including higher concentrations of carbon dioxide [8].

These environmental health risk factors can work synergistically with each other. For example, interactions between pollen and severe weather events can trigger public health emergencies such as epidemic thunderstorm asthma [9, 10]. Collectively, they translate into substantial economic burdens because of the increased demands on health services and reduced workplace productivity due to absenteeism [11–14]. Further, symptomatic allergic rhinitis, is also associated with impaired learning and reduced examination performance [15, 16]. Allergic diseases overall have been estimated to cost the Australian economy $30 billion per year [17]. Wholesale pharmacy purchases for allergic rhinitis medications, such as oral anti-histamines and nasal corticosteroids, doubled between 2001 and 2010 to $226.8 million [18].

The large geographic areas affected by hazards such as air pollution or airborne allergens, the potentially high number of people exposed, and the difficulty in stemming the exposures present serious public health management challenges. Public information and advisories, typically disseminated via print and electronic media and more recently through electronic notification systems, are a central component of responses to mitigate the human impacts of environmental hazards [19]. There are currently few systems where health advisories are specifically tailored to match the vulnerabilities of individuals; however, individually targeted systems have been shown to be more effective for health interventions than generic broadcast messaging. For example, Licskai *et al* [20] demonstrated that receipt of personal notifications of real-time and forecast local air quality was associated with substantial reductions in symptom criteria for uncontrolled asthma.

In this context, smartphone technologies offer significant potential to improve public health responses to atmospheric hazards by enabling the delivery of customised, easily accessible health information. Such digital applications are being increasingly used by patients with chronic medical conditions where symptoms, treatments, and test results can be presented in graphical displays either by individual or aggregated population groups as a part of 'quantified self-tracking' [21, 22]. Additionally, simple feedback to app users can be provided in response to reported information. Apps that provide early detection of clinical deterioration can enable personalised adjustment to treatment plans and improve health [23, 24]. Other examples of environmental digital health tools include the mining of social media data to identify smoke affected areas [25], and using crowd-sourced symptom data for the surveillance of influenza-like illness [26]. Marks [27] has argued the case for extending these methods to address the need for systematic syndromic symptom surveillance to enable a rapid response to epidemic thunderstorm asthma or other emerging health threats. Overall, the strong potential for smartphone technologies to reduce the health impacts of environmental and atmospheric health hazards is clear.

The use of smartphone technology in health care is a rapidly expanding field. Boulos *et al* [28], identified a range of apps for medical providers, speciality or disease-specific apps, medical education and teaching apps, along with apps for patients and the public but none integrated environmental conditions with the symptom data. Some examples of smartphone apps for allergic conditions [29], specific exposures and outcomes such as pollen and allergic rhinitis symptoms [30], or air pollution and asthma symptoms [20], have since been published. However, we could not find other examples where smartphone technology is used to integrate individual health symptoms with multiple environmental conditions in near real-time, in order to characterise individuals' specific sensitivities and generate customised notifications. Here we describe the first 22 months of the operation of AirRater, an integrated online platform that combines environmental monitoring and symptom surveillance via a free smartphone app. In 2015 it was launched in Tasmania, a temperate island state south of mainland Australia, where forest fires and winter wood heating are common episodic causes of poor air quality. AirRater's aims were to improve quality of life for people with asthma, allergic rhinitis, and other conditions affected by smoke, pollen and air temperature. First, we describe the architecture of the AirRater platform, outline the methods used for collecting, integrating and reporting environmental data and describe the smartphone application interface for communication with users. We then briefly summarise environmental conditions during the study period and report user uptake and engagement with the project through time, including perspectives gathered through evaluation surveys. Finally, we discuss the potential utility and limitations of the system for providing easily accessible environmental information, and supporting individual self-management, clinical care and public health practice.

Methods

Structure of the AirRater platform

AirRater is an integrated system (see figure 1) that tracks exposure to three key environmental hazards—air

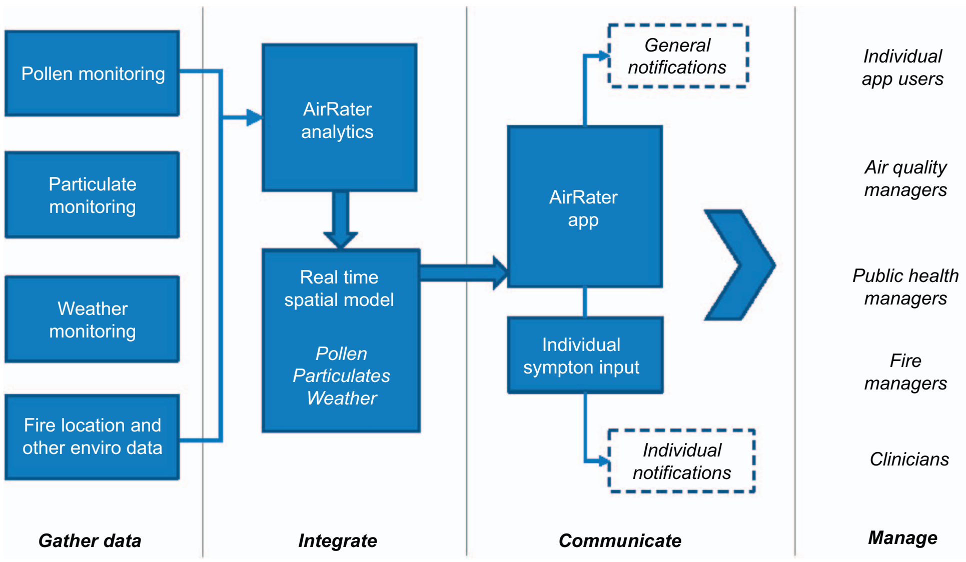

Figure 1. Schematic representation of the AirRater platform.

particles ($PM_{2.5}$), aeroallergens and temperature—and communicates these to participants via a set of interpolated maps, which can be viewed via a smartphone app or online interface. The app also allows individuals to report their symptoms in real-time from specific locations. These symptom reports are archived with co-located exposure estimates, and once sufficient records are recorded, automatic statistical analyses evaluate associations between a user's symptoms and specific environmental factors. This enables AirRater to provide users with tailored notifications, as well as support them to better understand and manage their health, often in partnership with their clinician. In addition, the AirRater platform uses a range of communication tools to support public health and environment agencies to respond to potential environmental health hazards at a community scale. The app is available for iOS and Android mobile platforms and on the web.

Data gathering and spatial integration of environmental exposures

AirRater draws environmental data from a number of sources. These include $PM_{2.5}$ data from the Environment Protection Authority (EPA) Tasmania, pollen data from AirRater-operated sites around Tasmania, and weather data from EPA Tasmania and the Australian Bureau of Meteorology.

Particle monitoring

AirRater draws particle ($PM_{2.5}$) data from the Baseline Air Network of the EPA Tasmania (BLANkET), see figure 2(*d*) [31]. These data are available at 10 minute intervals from 34 locations, including all major population centres. AirRater uses these data to spatially model 10 minute and hourly average $PM_{2.5}$ concentrations across Tasmania, using ordinary Kriging [32] to interpolate values between monitoring sites.

Pollen monitoring

Pollen and spore data are collected from six AirRater-operated sites (figure 2(*c*)) using a Burkard volumetric sampler (Burkard Manufacturing Co. Ltd, Hertfordshire) with either a daily (two sites) or weekly (four sites) sampling head [33].

Twenty seven pollen and one fungal taxon are counted individually (table S1 available at stacks.iop.org/ERL/13/044019/mmedia), with remaining taxa contributing towards the total pollen count. Within the app, users have access to the total pollen count along with six priority taxa: Poaceae (grasses); Myrtaceace (Eucalypt family); Cupressaceae (cypress family); *Betula* (birch); *Acacia* (wattle); *Alternaria* (an allergenic fungal spore) and *Plantago* (plantain). These taxa were selected based on their allergenic potential and local abundance [33–37]. Pollen counts are converted to atmospheric concentrations (grains m^{-3}) and expressed as a daily mean value [38]. State-wide map surfaces for the total pollen concentration and key taxa of interest are interpolated using inverse distance weighting.

Weather monitoring

The EPA Tasmania operate automatic weather stations at each BLANkET station, which provide air temperature, wind speed, relative humidity, precipitation and atmospheric pressure to the AirRater environmental database at 10 minute intervals. In addition, we acquire meteorological data for the same variables at half-hour intervals from the Australian Bureau of Meteorology (figure 2(*d*)). Temperature data is spatially interpolated across Tasmania using regression-Kriging with elevation as a covariate, while other variables are assigned to user symptom reports based on proximity to the closest station.

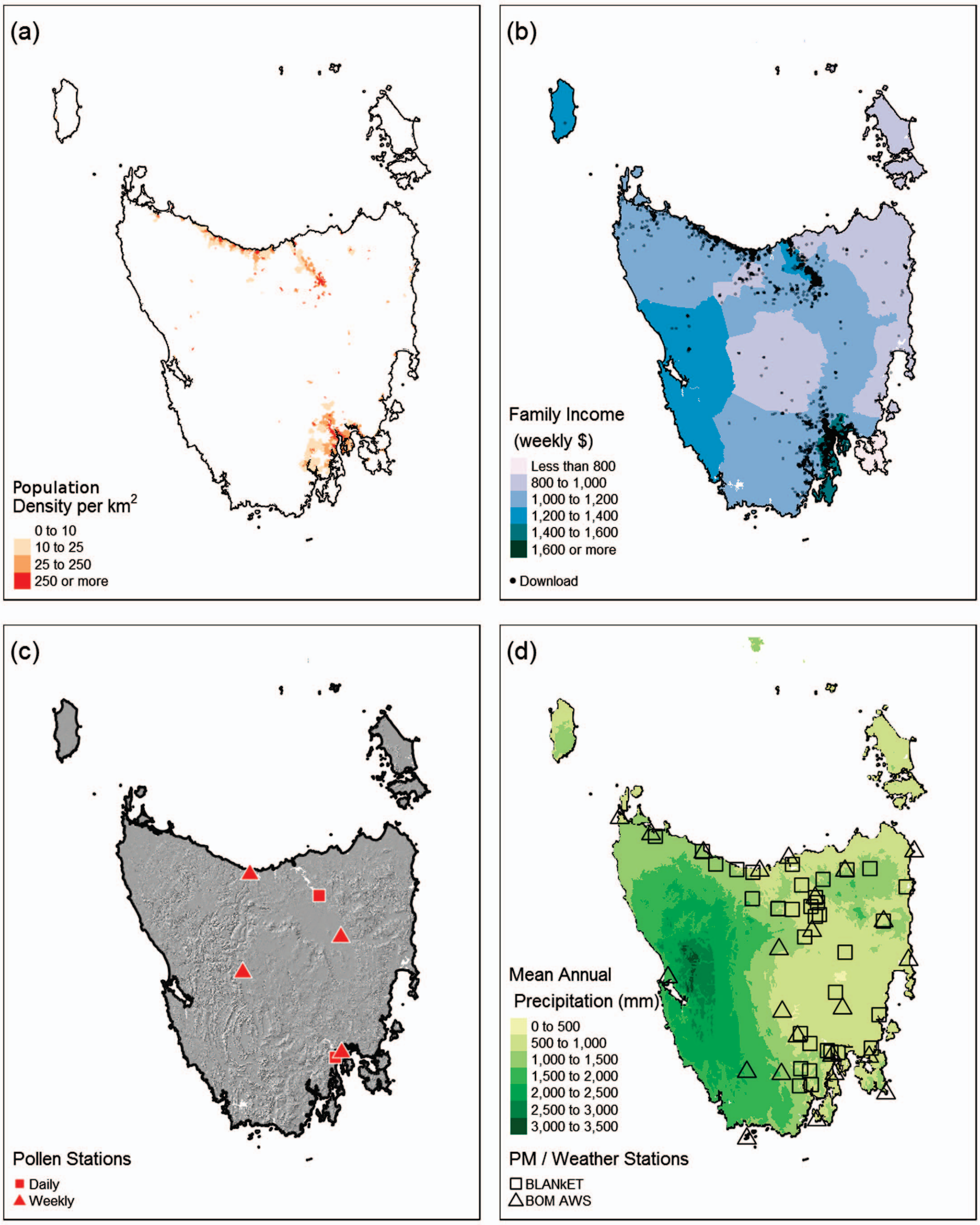

Figure 2. Population density, median income, and yearly rainfall distribution, highlighting the location of the environmental monitoring stations and the location of app downloads across Tasmania. (*a*) Population density per Km^2. (*b*) Location of downloads by socioeconomic status of region indicated by median family income ($/week). (*c*) Locations of daily and weekly pollen monitoring stations. (*d*) Locations of BLANkET PM and Bureau of Meteorology air weather stations (BOM AWS) and shading of rainfall as mean annual precipitation (mm). The dense air monitoring networks (*d*), throughout the populated areas (*a*) result in excellent population coverage for air quality data with more than half of the population (56%) living within 5 km of a monitor, 77% within 10 km and 95% within 20 km. For the pollen sites (*c*), 21% of the population live within 5 km of monitor, 50% within 10 km and 70% within 20 km of a monitor.

User interaction

Users have the ability to interact with the AirRater system in a number of ways—at sign up, through symptom reporting, by receiving notifications, and through evaluation opportunities. These are available via the smartphone app or online.

At signup, users have the choice of remaining anonymous, registering, or identifying as study participants. *Anonymous users* can create saved locations via the app, report symptoms and receive notifications of changing environmental conditions for their current and any saved locations. No identifying data is recorded. *Registered users* create an account and complete a registration questionnaire at signup. The survey includes information about their health and smoking status, history of asthma or allergic rhinitis, quality of life, gender and age. Detailed information about ethical approvals governing the project, data collection, data storage and privacy confidentiality arrangements are all provided in the end-user licencing agreement, which is agreed to at the time of registration. Registered users are able to restore their personal data if their device gets lost or broken or they move their account onto a new device, as they are identified in the system by their email address. *Study participants* are registered users who have additionally agreed to be notified of opportunities for participating in future research projects using AirRater. Study participants are required to submit a symptom report before environmental data is displayed in order to avoid symptom reports being systematically biased by knowledge of the current environmental conditions.

Symptom reporting

Individual users submit symptom reports at any time via the smartphone app. Each report requires selecting the area affected (e.g. nose, eyes, lungs) and the severity of the symptoms (mild, moderate or severe) to be logged. Optional additional information includes: specific symptoms (such as cough or itchy eyes), current cold or flu symptoms, presence of known triggers (e.g. pets), and use of medications (e.g. asthma reliever or antihistamine tablets). Symptom reports are tagged with the real-time environmental conditions at the user's geographic location and saved. If no reports have been submitted for a 6 day period, a notification is sent asking if the user has 'Any symptoms right now?'

When reporting a symptom, there is an option in the app to say 'Any triggers present now?' A prepopulated list includes options for 'exercise', 'dust', 'animal contact' and 'stress', with the option of 'Something else?'. Under this option, the user has additional options of 'mould', 'food and/or drink', 'cold air', 'head cold or flu' and 'not sure'. Users can also add their own known triggers to this list.

User notifications

Notifications are sent to users located in areas experiencing elevated $PM_{2.5}$ or pollen counts based on predefined thresholds. Users can turn these off or set the notification level to a lower or higher threshold. For example, the 10 minute $PM_{2.5}$ threshold is set to 15 $\mu g\,m^{-3}$ for low-, 25 $\mu g\,m^{-3}$ for medium-, and 50 $\mu g\,m^{-3}$ for high-threshold users respectively. Daily pollen thresholds are set to 50 grains m^{-3} for low-, 75 grains m^{-3} for medium-, and 100 grains m^{-3} for high-threshold users respectively. Notifications are not provided for current temperature. However, when an extreme coldwave or heatwave is forecast, as defined by the Excess Heat Factor algorithm used by the Australian Bureau of Meteorology [39], a notification is provided to users in the relevant location.

Once every twenty-four hours, a statistical model using weighted linear discriminant analysis is run for each individual and each of their symptoms. This correlates their reported symptoms, or absence of symptoms, with environmental data. If a user has more than 20 symptom reports, the predictor variables included are $PM_{2.5}$ concentration, total pollen count, temperature and relative humidity. The individual model for each user is assessed using a Kappa score, as an internal aspect of the AirRater app functionality. After the weighted linear discriminant analysis is performed for each user, the correctness of classification is assessed with Kappa, and only users with a Kappa of >0.6 (indicating good predictive power in the model) are sent notifications warning of adverse environmental conditions. The predictive model for these reports is run once an hour for relevant users.

User evaluation

We evaluated the use of the AirRater app using information from the following sources: (a) Apple and Google store data, which report the daily number of app downloads, the AirRater server which logs the number of unique users, daily usage, and symptom reports; (b) the registration questionnaire (described above), which includes health and demographic information; and (c) user evaluation surveys. All registered users with at least one month of experience were invited to participate in online evaluation surveys. Respondents were included in a draw to win a gift voucher in an attempt to increase uptake. These surveys sought feedback on the usefulness and functionality of the app, and how and when it had been used to manage symptoms. The surveys were conducted 3, 9 and 12 months after launching the app. In the third evaluation survey, we compared the recalled presence of symptoms in the previous four weeks with the number of symptom reports to the app by the same user in the same four-week period.

The project was approved by the Human Research Ethics Committee of the University of Tasmania H0015006.

Results

Our results cover two main areas: the environmental exposures experienced during the study period for particulate matter, pollen and temperature; and user uptake and engagement with the app as measured by recruitment levels, symptom reporting, and the results of user evaluation surveys.

Environmental exposures during the study period

The weather was typical of a temperate climate with mild summers and cool winters. There were no periods of extreme heat or cold during the study period. Elevated $PM_{2.5}$ was more frequent during winter months in all built-up locations where residential heating with wood is prevalent. In summer and autumn, landscape fires contributed to short periods of high concentrations of $PM_{2.5}$ in all major population centres in Tasmania. There were episodes of extreme $PM_{2.5}$

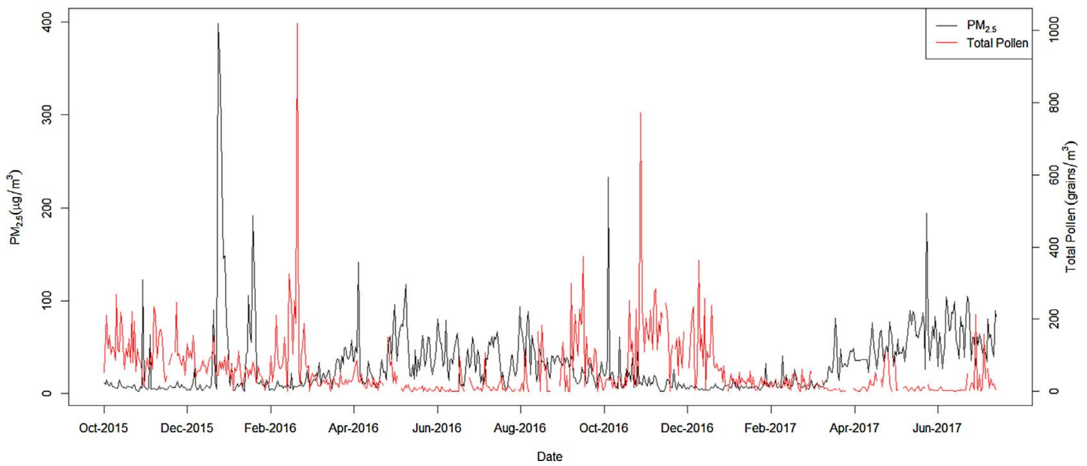

Figure 3. Daily mean $PM_{2.5}$ and total pollen concentrations for Northern Tasmania, October 2015–August 2017. The black line ($PM_{2.5}$) illustrates the seasonal increase in air pollution from domestic wood heaters from May to August each year, and intermittent brief spikes due to smoke from bushfires and planned burns throughout the study period. The red line (pollen) demonstrates the large day-to-day variation in pollen concentrations with an overall pattern of higher concentrations in spring and summer, and lower concentrations during autumn and winter.

concentrations associated with extensive and prolonged wildfires in January 2016 [40], especially across northern Tasmania (figure 3).

The total monthly and daily pollen concentrations followed a broadly similar seasonal pattern across the state. In both years, the pollen concentrations rose steeply from August, reflecting the onset of flowering in European trees and the predominantly exotic Cupressaceae (cypress) family. Monthly mean pollen levels remained relatively high until December (early summer), with daily pollen peaks regularly exceeding 100 grains m^{-3} and at times exceeding 500 grains m^{-3} at all sites. From November, the major driver of pollen abundance transitioned from exotic tree taxa to grass and total counts were low from March onwards (figure 3). While the two pollen sites within the city of Hobart showed a broadly similar seasonal progression, there were often notable daily differences in both the timing and magnitude of pollen peaks. Despite this, on greater than 85% of days, the pollen concentrations at the two sites fell into the same broad categorical level of exposure either low (< 15 grains m^{-3}), medium (15–49), high (50–99), extreme(100+). Peaks were not consistently higher at one site compared with the other.

User uptake and engagement

Recruitment

During the reported study period, Apple and Google store data reported 3,443 downloads of the AirRater app. AirRater server data reported 1,959 (57%) of downloads as registered users. Of those who registered, 48% reported having a medical diagnosis of asthma, 65% reported allergic rhinitis, 34% reported both asthma and allergic rhinitis, and 11% reported that they cared for a child or other person with one of these conditions. Most registered users were female (72%) with ages ranging from less than 1 to 73 years. Overall, the proportion of users who elected to register stayed relatively constant through time (figure 4(*a*)). Of these, 48% also elected to be study participants.

App downloads spiked in January 2016, coinciding with severe bushfires and associated episodes of poor air quality across the state, and again in late December 2016 coinciding with many media reports of hay fever and media promotion by the Department of Health and Human Services (figure 4(*a*)). Once this event passed (end of February 2016) the number of active users reduced.

Symptom reporting

Registered users provided the majority of symptom reports (94%). Almost 1,300 users made at least one symptom report during the study period, with 294 users making between 10 and 100 reports, and 27 reporting more than 100 times. Most reports related to nasal symptoms ($n = 5{,}251$ or 42%) followed by eyes ($n = 3{,}578$ or 29%), lungs ($n = 2{,}247$ or 18%) and throat ($n = 904$ or 7%). Large spikes in symptom reports were associated with spikes in downloads following publicity in local media (figure 4(*b*)). Because there was considerable variation in the number of people who used the app through time, we defined *active users* as the number of individuals that had used the app in the preceding week regardless of making a symptom report. Among active users, the rate of symptom reporting fluctuated but there were some clear spikes that coincided with severe smoke episodes (figure 5). Mean daily symptom reports per 100 active users varied seasonally, with the highest proportion in spring (72%), followed by winter (42%), summer (40%) and then autumn (37%).

Evaluation

The average response rate in the three evaluation surveys over the course of the study was 25%. Respondents

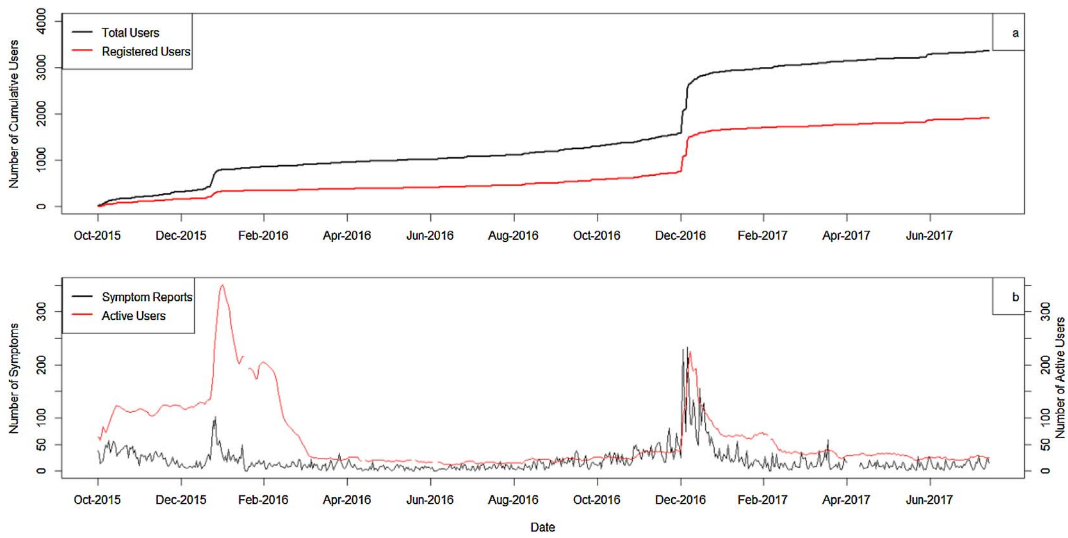

Figure 4. (*a*) Total cumulative downloads (black), and registered users (red); (*b*) daily number of symptom reports (black) and weekly moving average of active users (red).

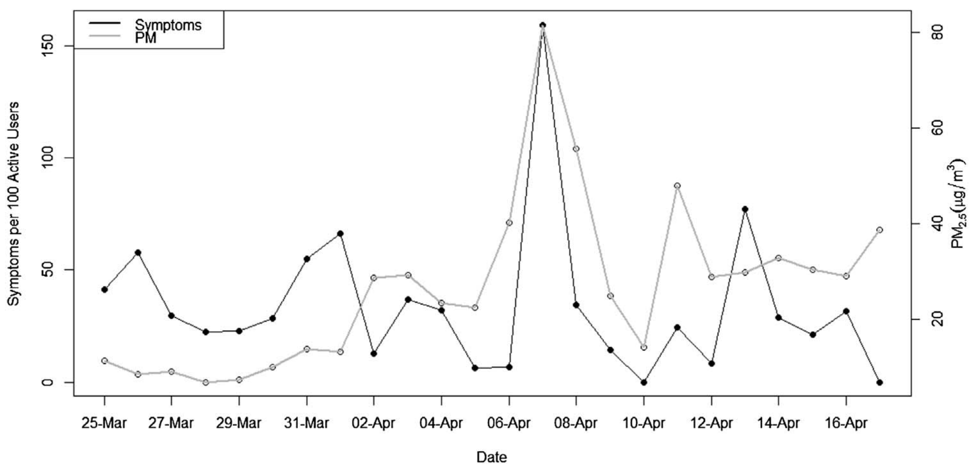

Figure 5. Number of reported symptoms per 100 active users (black) and Northern Tasmania mean daily $PM_{2.5}$ (grey) from March 25th–April 17th 2017 showing reduced air quality from planned burning on 7 April 2017.

found out about the app through social media (31%), traditional media (21%) and word of mouth (17%). Based on a five point Likert scale, from 'no use' to 'extremely useful', just 6% of respondents said the app was of no use, while 50% rated it as either 'very' or 'extremely' useful for their needs. The feature of the app rated as the most useful was access to daily pollen data (63%), followed by notification of reduced air quality in saved locations (39%). After eight or more months of use, most respondents (65%) reported that they were more aware of how their environment influenced their health. Around a third (30%–36%) had used information from the app to support decisions about their medications, outdoor activities or home environment, and a few (11%) had discussed their results with health professionals (figure 6). These results suggest that the app was prompting positive changes in behaviour to improve health. Free text comments were provided by 34% of respondents. These were overwhelmingly positive and many suggestions were subsequently incorporated into later versions of the app.

Comparison of symptom reporting between the app and survey

Only 25% of respondents who reported symptoms in the previous four weeks in the survey also logged symptoms via the app during the same period. However, 97% of respondents who reported 'no symptoms in the previous 4 weeks' in response to the survey, also did not log symptoms via the app in the same time period (table 1). This confirmed our expectation that symptoms, if present, were only reported some of the time, but we did not have further information to determine what influenced a user's decision to report.

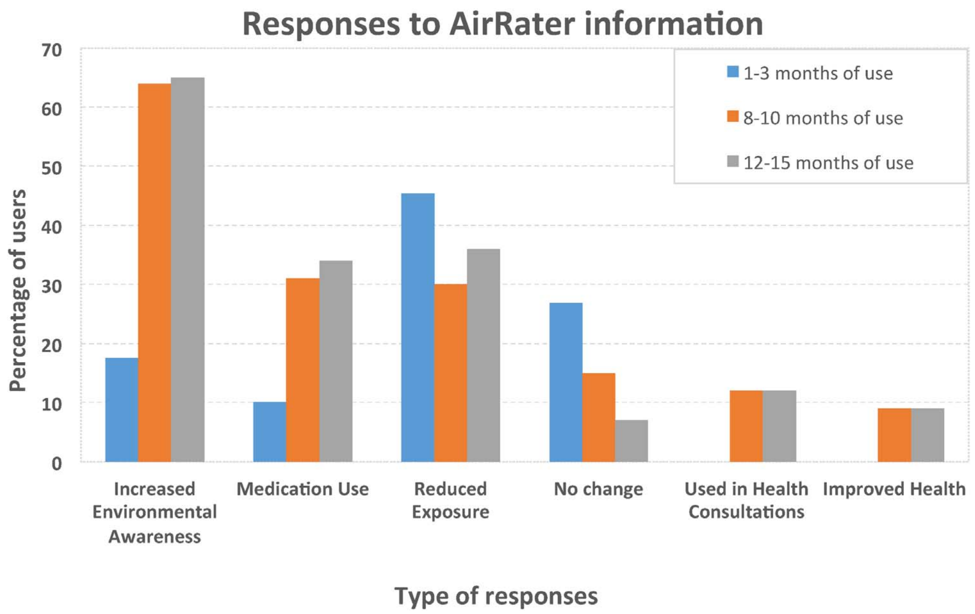

Figure 6. Responses to information from AirRater by length of time since downloading the app. Participants could report more than one response. Responses were categorised into the following six general groups:
Increased environmental awareness—Respondents reported becoming more aware of the environment and how it influences their health.
Medication use—Respondents had taken preventive medication.
Reduced exposure—Respondents had changed planned activities or altered their environment, e.g. by closing the doors and windows of their home.
No change—Respondents had not done anything differently as a result of using AirRater.
Used in health consultations—Respondents had referred to their use of the app with their doctor or other health professional when discussing their health issues.
Improved health—Respondents reported that using AirRater had improved their health.

Table 1. Reported symptoms in the last 4 weeks via the app compared with survey responses for the same period.

Symptoms (last 4 weeks)	Survey response that symptoms were not present in the past 4 weeks	Survey response that symptoms were present in the past 4 weeks	Total
No Airrater symptom reports in 4 weeks prior to survey	29	185	214
Any AirRater symptom reports in 4 weeks prior to survey	1	60	61
Total	30	245	**275**

Discussion

AirRater is an integrated monitoring, modelling and communication tool that provides individuals and agencies with near real-time, spatially-resolved information on exposure to pollen, air pollution (including smoke) and climatic stressors, and allows individuals to enter symptom data (figure 1). Access to such data from a single source in a user-friendly format has not been previously available.

This study demonstrates the value of this functionality to participants, especially the capacity for generating individual-level information about associations between health symptoms and a range of different environmental hazards. Another clear benefit of the AirRater platform is that it is building an integrated epidemiological dataset for investigating the association of multiple environmental exposures and symptoms among a population of high-risk individuals. This will be potentially useful for public health agencies in understanding the epidemiology of environmental exposures, and developing strategies for managing the impact of environmental health events [41]. Overall, the system is providing a combination of individual health management support and epidemiological intelligence.

However, a number of important knowledge gaps and technical challenges must be addressed to enable translation of AirRater's demonstrated potential into a sustainable risk management tool applicable in multiple settings as discussed below. These include objective verification of health benefits, and the provision of accurate exposure estimation where robust monitoring data are not available through dense monitoring networks.

While app users strongly endorsed the AirRater app because of perceived health benefits, objective verification of health benefits is required to demonstrate the health management value of these types of tools [20, 22, 42]. Measurable health benefits are challenging to demonstrate because of the nature of the data collected through smartphone applications. Key issues include inconsistent usage by individuals through time, retention of users, and the difficulty of evaluating reporting bias such as increases in reporting associated with obvious environmental events. Our experience during periods of extreme events suggests that downloads of the app increased substantially when media reports suggested that the AirRater app is a helpful tool, however when these extreme events had passed continued engagement was challenging. Evaluations also need to address the accessibility of the technology to better understand its role in public health planning and responses: uptake can be uneven because of limited access to smartphone technology, local internet access, or familiarity with digital technology in older age groups or groups from language backgrounds different to that used in the app. AirRater had strong uptake and active use, with similar uptake across all geographical regions including regions of low population density and contrasting socio-economic status (see figures 2(*a*) and (*b*)). This is in contrast to other studies which have shown that health apps are more often used by those from higher socioeconomic and health literate groups [43]. Noting that evaluation of app data alone cannot provide information about non-users, such limitations must be addressed in population level epidemiological studies based on crowd-sourced data [44].

Robust environmental exposure estimates are fundamental to the validity of any such tool. Access to environmental information was one of the most useful features of AirRater reported in the user evaluations. In Tasmania, real-time air quality data are available for all populated regions and this is especially useful during planned burns and bushfires when smoke pollution can rise and fall rapidly [45]. However, such comprehensive monitoring networks are unavailable in many other regions or nations. The development and incorporation of modelled forecasts based on remote sensing of active fires and other indices of air quality could address this limitation for poorly monitored locations, as could the availability of low cost air quality sensors [46].

Providing reliable estimates of concentrations of airborne allergens is another challenge for broadening the use of AirRater or similar surveillance networks. Pollen apps are common in North America and Europe, and are available for parts of Australia. Although many provide forecasts, few are based on accurately measured aeroallergens or validated forecasting methods [47]. In Australia, availability of this information is largely dependent upon sparsely located, university-based research teams [48]. Some monitors operate for a few months of the year, are restricted in the range of taxa that they report and most display either grass or total pollen counts rather than separate taxa. The advantage of AirRater, like many European pollen apps, is that multiple common taxa are reported, and participants can then use the correlation with symptoms to make behavioural changes to reduce their health impacts [30]. While only 11% of participants in this study reported that they discussed results with their health professional, there is potential for the data generated by AirRater to inform more evidence-based decisions around pollen treatment including immunotherapy [49]. There is a clear case for providing multi-taxon, geographically specific aeroallergen exposure estimates. However, identifying and counting pollen is labour intensive and costly, and providing such data is often cost-prohibitive. Finding ways to sustainably provide accurate, current and forecast pollen conditions for large or geographically dispersed populations is a high priority for environmental health research. While there have been promising advances in automated fluorescence and machine-learning pollen image classification [50, 51], as yet there are no cost-effective, scientifically-validated automated pollen monitors available for deployment. An alternative approach is phenological modelling combined with remote sensing to estimate the timing, magnitude and spatial distribution of pollen release from allergenic taxa. This has the virtue of providing spatially explicit pollen predictions. Studies from the northern hemisphere demonstrate that such an approach has strong potential [52, 53].

Conclusion

Monitoring and managing environmental hazards will become increasingly important as exposures continue to increase with global climate change. While there is potential for considerable individual, clinical and wider public health benefits from smartphone apps such as AirRater, it is essential that environmental data are reliable and validated. The way in which individual users interact with and report data need to be better understood before conclusions about individual or public health benefits can be drawn. Improved monitoring of air quality and pollen, especially the incorporation of short-term forecasting, will increase the functionality of such systems. Future approaches for incorporating highly spatially resolved data could include a tiered monitoring approach that integrates gold standard regulatory monitoring with automated sensor technology, remote sensing and modelling estimates. Nonetheless, we conclude that digital technologies offer considerable promise in supporting the public health management of environmental health hazards and in supporting individuals to manage health conditions sensitive to changes in the environment.

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Conflict of Interest: The authors declare they have no conflict of interest.

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References

[1] Pope C A and Dockery D W 2006 Critical Review. Health effects of fine particulate air pollution: Lines that connect *J. Air Waste Manage. Assoc.* **2006** 709–42
[2] Guo Y *et al* 2017 Heat waves and mortality: a multicountry, multicommunity study *Environ. Health Perspect.* **125** 087006
[3] Hajat S, Chalabi Z, Wilkinson P, Erens B, Jones L and Mays N 2016 Public health vulnerability to wintertime weather: time-series regression and episode analyses of national mortality and morbidity databases to inform the cold weather plan for England *Publ. Health* **137** 26–34
[4] De Sario M, Katsouyanni K and Michelozzi P 2013 Climate change, extreme weather events, air pollution and respiratory health in Europe *Eur. Respir. J.* **42** 826–43
[5] Liu J C *et al* 2016 Particulate air pollution from wildfires in the Western US under climate change *Clim. Change* **138** 655–66
[6] Ziello C *et al* 2012 Changes to airborne pollen counts across Europe *PLoS ONE* **7** e34076
[7] García-Mozo H 2017 Poaceae pollen as the leading aeroallergen worldwide: a review *Allergy* **72** 1849–58
[8] Field C B, Barros V R, Mach K and Mastrandrea M 2014 *Climatechange 2014: Impacts, Adaptation, and Vulnerability* (Cambridge: Cambridge University Press)
[9] Beggs P J 2017 Allergen aerosol from pollen-nucleated precipitation: A novel thunderstorm asthma trigger *Atmos. Environ.* **152** 455–7
[10] Lindstrom S J *et al* 2017 Thunderstorm asthma outbreak of November 2016: a natural disaster requiring planning *Med. J. Aust.* **207** 235–7
[11] Zuberbier T, Lötvall J, Simoens S, Subramanian S and Church M K 2014 Economic burden of inadequate management of allergic diseases in the European Union: a GA2LEN review *Allergy* **69** 1275–9
[12] Zander K K, Botzen W J, Oppermann E, Kjellstrom T and Garnett S T 2015 Heat stress causes substantial labour productivity loss in Australia *Nat. Clim. Change* **5** 647–51
[13] Kjellstrom T, Briggs D, Freyberg C, Lemke B, Otto M and Hyatt O 2016 Heat, human performance, and occupational health: a key issue for the assessment of global climate change impacts *Annu. Rev. Publ. Health* **37** 97–112
[14] Neidell M 2017 Air pollution and worker productivity *IZA World Labor* 363
[15] Walker S, Khan-Wasti S, Fletcher M, Cullinan P, Harris J and Sheikh A 2007 Seasonal allergic rhinitis is associated with a detrimental effect on examination performance in United Kingdom teenagers: case-control study *J. Allergy Clin. Immunol.* **120** 381–7
[16] Trikojat K, Buske-Kirschbaum A, Plessow F, Schmitt J and Fischer R 2017 Memory and multitasking performance during acute allergic inflammation in seasonal allergic rhinitis *Clin. Exp. Allergy* **47** 479–87
[17] Cook M, Douglass J, Mallon D, Mullins R, Smith J and Wong M 2007 The economic impact of allergic disease in Australia: not to be sneezed at *Australas. Soc. Clin. Immunol. Allergy* (Sydney: Access Economics)
[18] Australian Institute of Health Welfare 2011 Allergic Rhinitis ('Hay Fever') in Australia. Canberra
[19] Kelly F J, Fuller G W, Walton H A and Fussell J C 2012 Monitoring air pollution: use of early warning systems for public health *Respirology* **17** 7–19
[20] Licksai C J, Sands T W and Ferrone M 2013 Development and pilot testing of a mobile health solution for asthma self-management: asthma action plan smartphone application pilot study *Can. Resp. J.: J. Can. Thorac. Soc.* **20** 301
[21] Milani R V, Bober R M and Lavie C J 2016 The role of technology in chronic disease care *Prog. Cardiovasc. Dis.* **58** 579–83
[22] Swan M 2009 Emerging patient-driven health care models: an examination of health social networks, consumer personalized medicine and quantified self-tracking *Int. J. Environ. Res. Publ. Health* **6** 492–525
[23] Anderson K, Burford O and Emmerton L 2016 App chronic disease checklist: protocol to evaluate mobile apps for chronic disease self-management *JMIR Res. Protoc.* **5**
[24] Wicks P *et al* 2010 Sharing health data for better outcomes on patients like me *J. Med. Internet Res.* **12**
[25] Ford B, Burke M, Lassman W, Pfister G and Pierce J R 2017 Status update: is smoke on your mind? Using social media to assess smoke exposure *Atmos. Chem. Phys.* **17** 7541–54
[26] Carlson S J, Dalton C B, Durrheim D N and Fejsa J 2010 Online Flutracking survey of influenza-like illness during pandemic (H1N1) 2009 *Aust. Emerg. Infect. Dis.* **16** 1960
[27] Marks G 2016 It's not just about Melbourne: why we need a national approach to thunderstorm asthma *Conversation* (https://theconversation.com/its-not-just-about-melbourne-why-we-need-a-national-approach-to-thunderstorm-asthma-69426)
[28] Boulos M N K, Brewer A C, Karimkhani C, Buller D B and Dellavalle R P 2014 Mobile medical and health apps: state of the art, concerns, regulatory control and certification *Online J. Publ. Health Inform.* **5** 229
[29] Bousquet J, Caimmi D, Bedbrook A, Bewick M, Hellings P and Devillier P *et al* 2017 Pilot study of mobile phone technology in allergic rhinitis in European countries: the MASK-rhinitis study *Allergy* **72** 857–65
[30] Kmenta M, Bastl K, Jäger S and Berger U 2014 Development of personal pollen information—the next generation of pollen information and a step forward for hay fever sufferers *Int. J. Biometeorol.* **58** 1721–6
[31] Environment Protection Authority Tasmania 2010 BLANkET: The Base-Line Air Network of EPA Tasmania Hobart
[32] Liao D *et al* 2006 GIS approaches for the estimation of residential-level ambient PM concentrations *Environ. Health Perspect.* **114** 1374

[33] Tng D Y P, Hopf F, Haberle S G and Bowman D M J S 2010 Seasonal pollen distribution in the atmosphere of Hobart, Tasmania: preliminary observations and congruence with flowering phenology *Aust. J. Bot.* **58** 440–52

[34] Hanigan I C and Johnston F H 2007 Respiratory hospital admissions were associated with ambient airborne pollen in Darwin, Australia, 2004–2005 *Clin. Exp. Allergy* **37** 1556–65

[35] Pablos I, Wildner S, Asam C, Wallner M and Gadermaier G 2016 Pollen allergens for molecular diagnosis *Curr. Allergy Asthma Rep.* **16** 31

[36] Gibbs J E 2015 Eucalyptus pollen allergy and asthma in children: a cross-sectional study in South-East Queensland, Australia *PLoS ONE* **10** e0126506

[37] Burbach G *et al* 2009 GA2LEN skin test study II: clinical relevance of inhalant allergen sensitizations in Europe *Allergy* **64** 1507–15

[38] Galán C, Smith M, Thibaudon M, Frenguelli G, Oteros J, Gehrig R, Berger U, Clot B, Brandao R and Working Group E A S Q C 2014 Pollen monitoring: minimum requirements and reproducibility of analysis *Aerobiologia* **30** 385–95

[39] Nairn J R and Fawcett R J 2014 The excess heat factor: a metric for heatwave intensity and its use in classifying heatwave severity *Int. J. Environ. Res. Publ. Health* **12** 227–53

[40] Marris E 2016 Tasmanian bushfires threaten iconic ancient forests *Nature* **530** 137–8

[41] Kmenta M, Zetter R, Berger U and Bastl K 2016 Pollen information consumption as an indicator of pollen allergy burden *Wien. Klin. Wochenschr.* **128** 59–67

[42] Huang X and Matricardi P M 2016 Allergy and asthma care in the mobile phone era *Clin. Rev. Allergy Immu.* 1–13

[43] Ernsting C, Dombrowski S U, Oedekoven M and Lo J 2017 Using smartphones and health apps to change and manage health behaviors: a population-based survey *J. Med. Internet Res.* **19** e101

[44] Stieb D M, Boot C R and Turner M C 2017 Promise and pitfalls in the application of big data to occupational and environmental health *BMC Publ. Health* **17** 372

[45] Environment Protection Authority Tasmania 2011 *Analysis of BLANKet $PM_{2.5}$ Data January–August 2010: Planned Burning and Domestic Woodheater Smoke* (Hobart: EPA)

[46] Mead M I *et al* 2013 The use of electrochemical sensors for monitoring urban air quality in low-cost, high-density networks *Atmos. Environ.* **70** 186–203

[47] Bastl K, Berger U and Kmenta M 2017 Evaluation of pollen apps forecasts: the need for quality control in an health service *J. Med. Internet Res.* **19** e152

[48] Davies J M *et al* 2016 ASCIA-P30: the AusPollen partnership: implementing a standardised national pollen alert system for better management of allergic respiratory health *Int. Med. J.* **46** 13–4

[49] Bianchi A, Tsilochristou O, Gabrielli F, Tripodi S and Matricardi P 2016 The smartphone: a novel diagnostic tool in pollen allergy? *J. Investig. Allergol. Clin. Immunol.* **26** 204–7

[50] Holt K A and Bennett K 2014 Principles and methods for automated palynology *New Phytol.* **203** 735–42

[51] Crouzy B, Stella M, Konzelmann T, Calpini B and Clot B 2016 All-optical automatic pollen identification: towards an operational system *Atmos. Environ.* **140** 202–12

[52] Duhl T, Zhang R, Guenther A, Chung S, Salam M and House J *et al* 2013 The simulator of the timing and magnitude of pollen season (STaMPS) model: a pollen production model for regional emission and transport modeling *Geosci. Model Dev. Discuss.* **6** 2325–68

[53] Sofiev M *et al* 2015 MACC regional multi-model ensemble simulations of birch pollen dispersion in Europe *Atmos. Chem. Phys.* **15** 8115